estat acplot - Plot parametric autocorrelation and autocovariance functions

Description	Quick start	Menu for estat	Syntax	Options
Remarks and examples	Methods and formulas	References	Also see	

Description

estat acplot plots the estimated autocorrelation and autocovariance functions of a stationary process using the parameters of a previously fit parametric model.

estat acplot is available after arima and arfima; see [TS] arima and [TS] arfima.

Quick start

Autocorrelation function using estimates from arima or arfima estat acplot

Autocovariance function using estimates from arima or arfima estat acplot, covariance

Same as above, and save results in mydata.dta estat acplot, covariance saving(mydata)

Menu for estat

Statistics > Postestimation

Syntax

estat acplot [, options]

Description
save results to <i>filename</i> ; save variables in double precision; save variables with prefix <i>stubname</i>
set confidence level; default is level(95)
use # autocorrelations
calculate autocovariances; the default is to calculate autocorrelations
report short-memory ACF; only allowed after arfima
affect rendition of the confidence bands
change look of markers (color, size, etc.)
add marker labels; change look or position
affect rendition of the plotted points
any options other than by () documented in [G-3] twoway_options

Options

saving(filename[, suboptions]) creates a Stata data file (.dta file) consisting of the autocorrelation
estimates, standard errors, and confidence bounds.

Five variables are saved: lag (lag number), ac (autocorrelation estimate), se (standard error), ci_l (lower confidence bound), and ci_u (upper confidence bound).

double specifies that the variables be saved as doubles, meaning 8-byte reals. By default, they are saved as floats, meaning 4-byte reals.

name (stubname) specifies that variables be saved with prefix stubname.

replace indicates that *filename* be overwritten if it exists.

- level(#) specifies the confidence level, as a percentage, for confidence intervals. The default is level(95) or as set by set level; see [R] level.
- lags (#) specifies the number of autocorrelations to calculate. The default is to use $\min\{\operatorname{floor}(n/2) 2, 40\}$, where $\operatorname{floor}(n/2)$ is the greatest integer less than or equal to n/2 and n is the number of observations.

covariance specifies the calculation of autocovariances instead of the default autocorrelations.

smemory specifies that the ARFIMA fractional integration parameter be ignored. The computed autocorrelations are for the short-memory ARMA component of the model. This option is allowed only after arfima.

CI plot

ciopts (*rcap_options*) affects the rendition of the confidence bands; see [G-3] *rcap_options*.

Plot

marker_options affect the rendition of markers drawn at the plotted points, including their shape, size, color, and outline; see [G-3] *marker_options*.

marker_label_options specify if and how the markers are to be labeled; see [G-3] *marker_label_options*.

cline_options affect whether lines connect the plotted points and the rendition of those lines; see [G-3] *cline_options*.

Y axis, X axis, Titles, Legend, Overall

twoway_options are any of the options documented in [G-3] *twoway_options*, except by (). These include options for titling the graph (see [G-3] *title_options*) and for saving the graph to disk (see [G-3] *saving_option*).

Remarks and examples

The dependent variable evolves over time because of random shocks in the time domain representation. The autocovariances γ_j , $j \in \{0, 1, \dots, \infty\}$, of a covariance-stationary process y_t specify its variance and dependence structure, and the autocorrelations ρ_j , $j \in \{1, 2, \dots, \infty\}$, provide a scale-free measure of y_t 's dependence structure. The autocorrelation at lag j specifies whether realizations at time t and realizations at time t - j are positively related, unrelated, or negatively related. estat acplot uses the estimated parameters of a parametric model to estimate and plot the autocorrelations and autocovariances of a stationary process.

Example 1

In example 1 of [TS] **arima**, we fit an ARIMA(1,1,1) model of the US Wholesale Price Index (WPI) using quarterly data over the period 1960q1 through 1990q4.

<pre>. arima wpi, arima(1,1,1) (setting optimization to BHHH) Iteration 0: Log likelihood = -139.80133 Iteration 1: Log likelihood = -135.6278 Iteration 2: Log likelihood = -135.41838 Iteration 3: Log likelihood = -135.36691 Iteration 4: Log likelihood = -135.35892 (switching optimization to BFGS) Iteration 5: Log likelihood = -135.35135 Iteration 7: Log likelihood = -135.35132 Iteration 8: Log likelihood = -135.35132 Iteration 8: Log likelihood = -135.35131 ARIMA regression Sample: 1960q2 thru 1990q4 Number of obs = 123 Wald chi2(2) = 310.64 Log likelihood = -135.3513 Prob > chi2 = 0.0000 OPG D.wpi Coefficient std. err. z P> z [95% conf. interval] wpicons .7498197 .3340968 2.24 0.025 .0950019 1.404637 ARMA ar L18742288 .0545435 16.03 0.000 .7673256 .981132 ma L14120458 .1000284 -4.12 0.00060809792159938</pre>		/www.stata-pre		, , <u>F</u> = -	L		
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Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

Now we use estat acplot to estimate the autocorrelations implied by the estimated ARMA parameters. We include lags(50) to indicate that autocorrelations be computed for 50 lags. By default, a 95% confidence interval is provided for each autocorrelation.

. estat acplot, lags(50)



The graph is similar to a typical autocorrelation function of an AR(1) process with a positive coefficient. The autocorrelations of a stationary AR(1) process decay exponentially toward zero.

4

Methods and formulas

The autocovariance function for ARFIMA models is described in *Methods and formulas* of [TS] **arfima**. The autocovariance function for ARIMA models is obtained by setting the fractional difference parameter to zero.

Box et al. (2016) provide excellent descriptions of the autocovariance function for ARIMA and seasonal ARIMA models. Palma (2007) provides an excellent summary of the autocovariance function for ARFIMA models.

References

Box, G. E. P., G. M. Jenkins, G. C. Reinsel, and G. M. Ljung. 2016. *Time Series Analysis: Forecasting and Control.* 5th ed. Hoboken, NJ: Wiley.

Palma, W. 2007. Long-Memory Time Series: Theory and Methods. Hoboken, NJ: Wiley.

Also see

- [TS] **arfima** Autoregressive fractionally integrated moving-average models
- [TS] arima ARIMA, ARMAX, and other dynamic regression models

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